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Neural Network Cloud Classification Research

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ABSTRACT

Neural networks are appropriate for meteorological classification tasks for a number of reasons. First, their associative properties allow graceful degradation of performance under conditions of ambiguity and noise, thus avoiding the brittle behavior of many standard approaches. Second, they learn to perform tasks which cannot easily be specified analytically, such as non-linear discriminate functions. Finally, they can be executed in real-time on appropriate hardware. To exploit these properties, this research developed a general approach to meteorological classification based on neural network data fusion. The system was applied to cloud type identification from satellite imagery. The current experiment is one of the first to provide a *large* cloud database on which to train, and as such is one of the first true *cross-validation* experiments in this area. While the 27 days of data provides many pixel samples of the cloud types present at a particular hour, the question to be answered here was whether the samples collected on particular types of clouds sufficiently represent the variations of that cloud that can appear on a different day. The promising results point to the applicability of neural networks for automated generation of meteorological products in real-time.

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SECTION 1

INTRODUCTION

Neural networks are appropriate for meteorological classification tasks for a number of reasons. First, their associative properties allow graceful degradation of performance under conditions of ambiguity and noise, thus avoiding the brittle behavior of many standard approaches. Second, they learn to perform tasks which cannot easily be specified analytically. This allows improved performance in perception tasks and cost-effective retargeting of systems to additional domains. Finally, they can be executed in real-time on appropriate hardware. To exploit these properties, this research developed a general approach to meteorological classification based on neural network data fusion. The system was applied to cloud type identification from satellite imagery. Howevei, the system could easily be retrained to perform a range of other meteorological identification tasks such as the identification of hurricanes, thunderstorm outflow boundaries, etc.

A number of promising preliminary results for the method have been shown during the previous work [9,11], including a demonstration of accurate classification performance on a limited dataset, graceful degradation of classification performance over large shifts of terrain, and fusion of ground sensor data with meteorological imagery. Those initial experiments were jackknife tests performed on very small data sets. Jackknife tests cull their separate test data from the same source that provides the training data. Since cloud formations often span large distances, it is probably the case that the sample distributions of both training and test sets were similar. Most prior cloud typing experiments have been of similar small size and suffer from the same problems.

The current experiment is one of the first to provide a *large* database on which to train, and as such is one of the first true *cross-validation* experiments in this area. The current work applied and refined the original techniques to the large database. While the 27 days of data provides many pixel samples of the cloud types present at a particular hour, the question to be answered here was whether the samples collected on particular types of clouds sufficiently represent the variations of that cloud type that can appear on a different day. The promising results point to the applicability of neural networks for automated generation of meteorological products in real-time.

The system architecture is shown in figure 1. Heterogeneous sensor streams including point sensor data and/or image data are fed into the system. A vision system utilizing a number of biologically plausible theories produces a range of non-local products which augment the local training data for the neural network classifier stage. Point sensor data can be optionally extrapolated in two dimensions to match image data [11]. Supervised learning is used to train the classifiers. A large meteorological database provides the target signal for training. A knowledge-based system controls the performance elements of the classification system. The simplest implementation would be a look-up table indexed by time of day and

season. To allow the inclusion of meteorological heuristics, the control component may incorporate expert system technologies. Neural network-based control is also a possibility. Classification performance is measured by cross validation tests using untrained human classifications.

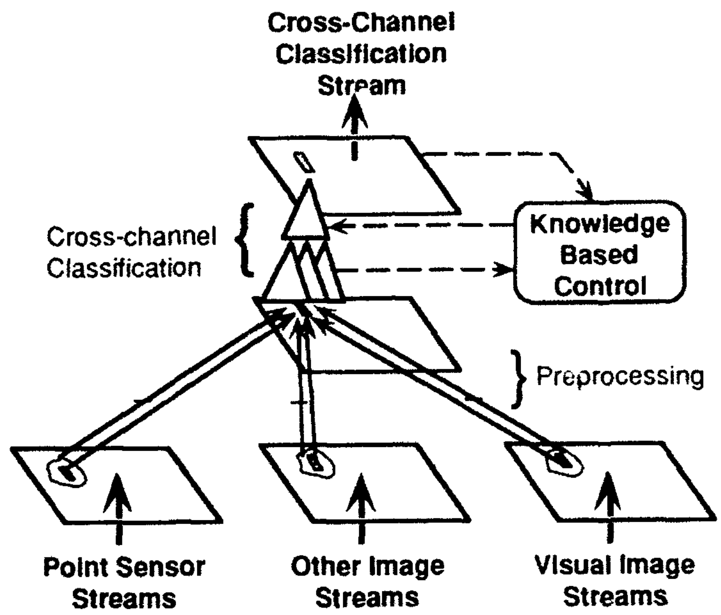


Figure 1. System Architecture

Feature vectors for classification are constructed by appending image data with derived products generated via a number of preprocessing steps. The derived products provide information of a non-local nature which is used as part of a classification which operates on local regions (i.e., pixels). Vision algorithms applied to the image data provide texture and morphology features.

The classifier uses a multiple module feedforward neural network. It implements a number of non-linear discriminate functions which are specifically tailored to the meteorological task to provide high accuracy and good generalization to untrained data.

1.1 RELATION TO PREVIOUS WORK

Garand [3], produced an extensive study which applied an extensive range of analytical image processing measures and a Multivariate Gaussian Discriminate function. Twenty cloud classes were used, including a number of special classes (e.g., Cloud Streets, Rolls, Polygonal Open Cells, and Strongly Convective Open Cells) and clear. Garand's study used

GOES-EAST data collected at 1600 UTC for 29 days during February 1984. The test set was comprised of 1800 UTC data for January 8 and 12, 1984 and February 7, 8, and 12, 1984. Only results for sea are reported. The method processed and reported results for 128 x 128 km regions. An overall accuracy of 79 percent was reported.

The current study used a subset of Garand's classification scheme and also used GOES-EAST data, but both land and sea data were included. A non-linear neural network discrimination function was used. No special estimates of physical parameters were used as features; complex discrimination surfaces are learned from the raw data, wavelet, and morphology features. Our method reports results for each pixel instead of for a large region, allowing more detailed cloud classification maps. The current study used test data from strictly unseen days whereas 3/5 of the Garand test data was from days that had been included in the training sample with two hours of difference in the samples.

Lee, et al. [8], produced a neural network study which demonstrated high mean accuracy using three cloud classes. The study used only Visible imagery and used an algorithmic texture feature called the Gray Level Difference Vector (GLDV). The standard backpropagation training algorithm was used. Their cumulus class ranged from small fair weather cumulus to mesoscale sized cumulus. Their cirrus class included cirrus, cirrostratus, cirrocumulus, and contrails. Their stratocumulus class ranged from solid decks to breakup regions. The study used LANDSAT MSS imagery with a spatial resolution of 57 m per pixel. Each image covers 185 km by 170 km. A mean accuracy of 94 percent was reported.

The current study also uses a neural network classifier. A subtractive learning algorithm specialized for generalization performance was used. Data from unseen days was used for testing. The high resolution LANDSAT MSS data provides more accurate texture information than the low resolution GOES data used for our study. The current study used eight cloud classes as opposed to three.

Bankert, et al. [1], produced a study which used the Probabilistic Neural Network (PNN) to classify clouds in Advanced Very High Resolution Radiometer (AVHRR) imagery. Ten cloud classes were used: Cirrus, Cirrocumulus, Cirrostratus, Altostratus, Nimbostratus, Stratocumulus, Stratus, Cumulus, Cumulonimbus, and Clear. All samples were obtained from a total of four 512 x 512 pixel images, two of which occur on the same day and time at locations separated by 14' latitude and 5' longitude. The feature vector contained 203 components, including the GLDV texture measure and a number of physical measures from Garand's study.

The current study uses a subtractive learning algorithm which constructs a compact representation from an unlimited number of samples. Techniques such as these can utilize large numbers of samples with low memory and low execution computational requirements. The PNN classifier constructs its representation of the sample distribution by retaining each sample in the training set in memory. The PNN approach limits the number of samples that can be used for training and thus effects the ultimate scalability of the technique. The

AVHRR resolution should provide improved texture discrimination capability over the GOES resolution used here.

1.2 EXPERIMENTAL GOALS

The major goal of the experiment was to test the generalization capabilities of the neural network classification system on completely independent untrained data. Another goal was to test the effectiveness of various algorithmic improvements. A final goal was to test various strategies for scaling the techniques to operational status.

1.3 EXPERIMENTAL PROCEDURE

1.3.1 Day Cloud Database

GOES-EAST satellite imagery was provided by the Phillips Laboratory, Geophysics Directorate. The data was collected from 1430 to 1900 GMT half hourly during June and July of 1991. The visible (0.55-0.75 µm) channel and (11 µm window) infrared channel were used. Images of size 512 x 512 pixels at 1 km resolution were used. Each image contained New England and the adjacent Atlantic ocean. The following thirteen cloud classes were used to classify the imagery:

1. Small Scattered Cumulus
2. Cumulus
3. Thin Cirrus
4. Cirrus
5. Thin Cirrus over cloud
6. Stratus
7. Stratocumulus
8. Altocumulus
9. Altostratus
10. Cumulonimbus
11. Clear
12. Haze
13. Fog

A computer method for manually classifying the image data sets and storing files of the results was devised. Classifications were selected while viewing visible. infrared, or a visible/infrared composite image. A mouse was used to sweep squares of a user selectable size (typically 12 pixels) across the image to mark cloud samples. Each sample had an associated color which encoded the cloud type. A menu bar along the edge of the display was used to select the desired cloud type. Mistakes were easily erased and corrected either during the initial session or later in a resumed session. The result of the process is a new

image file called a "Pick" file which contains the classification information in the selected pixel locations. As the analysts could not easily cover only the cloud cover for small cumulus clouds, a postprocessing step was run to eliminate cases where the clear space between cumulus clouds had been classified as cumulus.

Two consoles were used side by side. Two Phillips Laboratory Geophysics Directorate analysts manned the consoles and worked together to produce consensus classifications. Both analysts could see both displays. The screen on the left showed the current session. The screen on the right showed the previous half hour imagery with its Pick image superimposed. The right console was used to make modifications and additions as needed. Further details on the database are provided in [6].

The cloud database consists of ten samples per day taken at half hour intervals. Due to collection problems, a maximum of 27 samples is available for some hours and as few as 22 are available for other hours. To maximally utilize the data, a series of leave-one-out cross validation tests were run. In these 26 days of data were used for training and an unseen 27th day was used for testing. These were run at a single time 1700 across the days. Because certain cloud types had very few samples, they were left out of these experiments because generalization performance would be degraded by their inclusion. All examples of these cloud types were removed from the training and test sets. The resulting eight cloud classes and numbering scheme used for all results reported in the following is:

1. Small Scattered Cumulus
2. Cumulus
3. Thin Cirrus
4. Cirrus
5. Thin Cirrus over cloud
6. Stratocumulus
7. Altocumulus
8. Clear

Figure 2a shows a typical visible image of the sample region. Figure 2b shows the associated infrared image. There is about 60 percent land and 40 percent water for the New England area used.

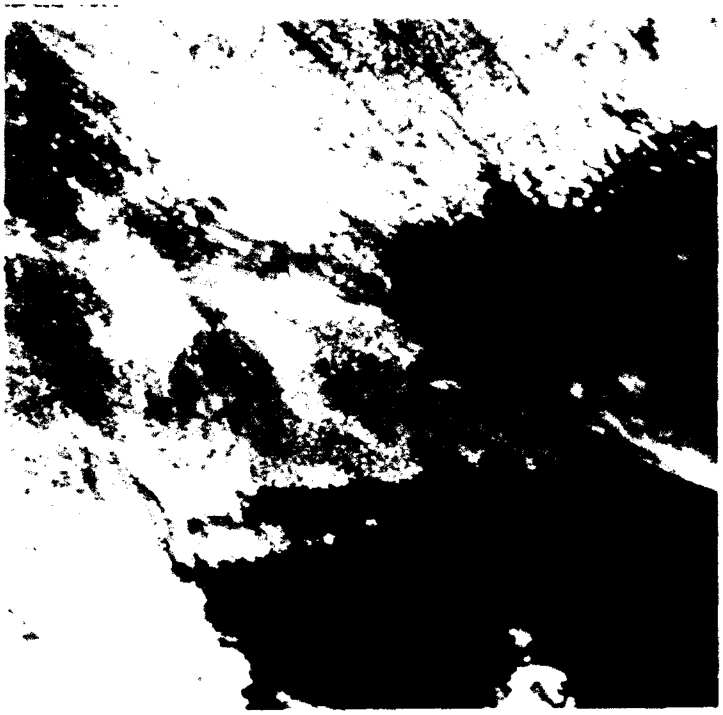


Figure 2a. Visible GOES Image for June 6, 1991 at 1730 GMT

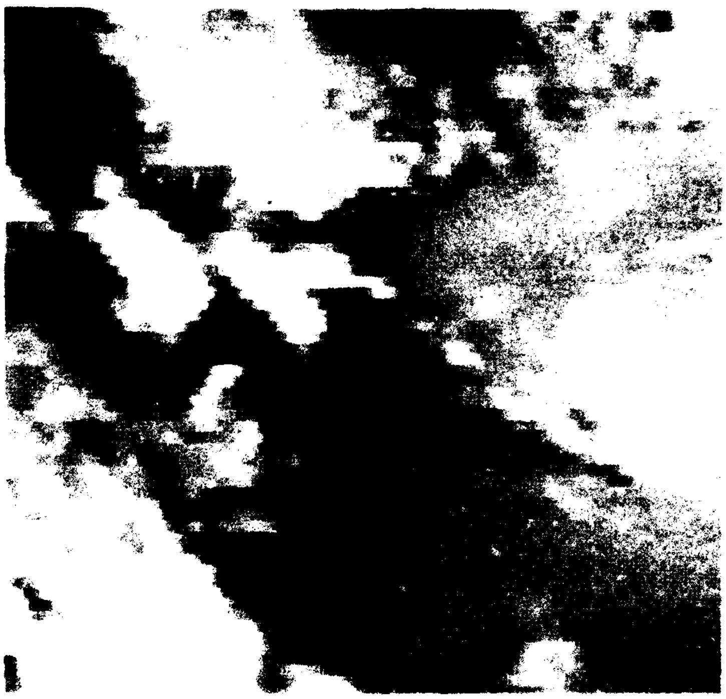


Figure 2b. Infrared GOES Image for June 6, 1991 at 1730 GMT

SECTION 2

PREPROCESSING STEPS

A comb filter was designed and implemented to remove scan lines from the original visual channel imagery. Feature vectors for classification were constructed by appending the Visible and IR local pixel data with derived products generated via a number of preprocessing steps. The derived products provide information of a non-local nature which is then used as part of the input to a classifier which operates on local regions (i.e., pixels). We developed a FFT version of the vision software that runs on Mercury vector processors which plug into Sun Sparcstation hosts. This step was necessary because of the large size (512 x 512) and large number of images we had to process for this experiment.

2.1 TEXTURE

The 2D Gabor wavelet transform introduced by Daugman [2] is an efficient conjoint Spatial/Spectral 2D information encoding. The 2D Gabor forms a non-orthogonal basis[1] which can be used for image coding. In addition, it has been shown to be useful for texture segmentation of imagery. Its characteristics model observed behavior of simple cells in mammalian optical cortex. Equation one specifies the general functional form of the 2D Gabor family in terms of the space-domain impulse response function G(x,y):

$$G(x,y)=e^{-\pi((x-x_0)^2a^2 + (y-y_0)^2b^2)} \times e^{-2\pi i(u_0(x-x_0) + v_0(y-y_0))} \qquad (1)$$

where (x,y) are position parameters and (u,v) are modulation parameters. A family of self-similar 2D Gabor wavelets were used for spatial frequency analyses which are combined by the feed-forward classifier network to form texture detectors. In the original experiments [9,11], six spatial frequencies spaced by half octaves were used for the Visible channel and four spatial frequencies spaced by half octaves were used for the IR channel. Each spatial frequency was represented by a quadrature phase pair in six orientations. The locality preserving nature of the 2D Gabor has been particularly useful for increased accuracy in texture detection.

2.1.1 Generalized Gabor Representation

Small sample sets might not have examples of each cloud type at all orientations. To eliminate the possible detrimental effects on classifier generalization performance, a compressed representation which eliminates orientation specificity was designed.

---

1 Gabors can form a quasi-orthogonal basis with appropriate spacing.

The data in the infrared channel has a very low frequency component which was judged to be of marginal utility to the classification of the current cloud types. The lowest frequency data in the visible image was similarly ignored. Thus, six orientations of Gabor wavelets at four spatial scales were used for the visible image and no Gabor data was used for the infrared image. To generalize the remaining data, the six oriented wavelet responses at each spatial scale were replaced by two values. The first is the root mean square value of the quadrature pair envelopes of all the oriented responses at a pixel location. This provides information as to the extent that clouds have texture at this spatial scale. The second representation indicates the degree to which the oriented response was localized or not. In this representation, the rms value is scaled by a variable which takes a value between +1 and -1, where +1 occurs if many striation angles were detected and -1 occurs where only one striation angle was detected. Thus the reduced representation indicates the degree to which a cloud sample has a specific striation at some orientation angle, but it eliminates the particular angle(s) from the data. Examples of the reduced representation for one spatial scale can be seen in figures 3 and 4. Eliminating the irrelevant angle information greatly improved generalization performance.

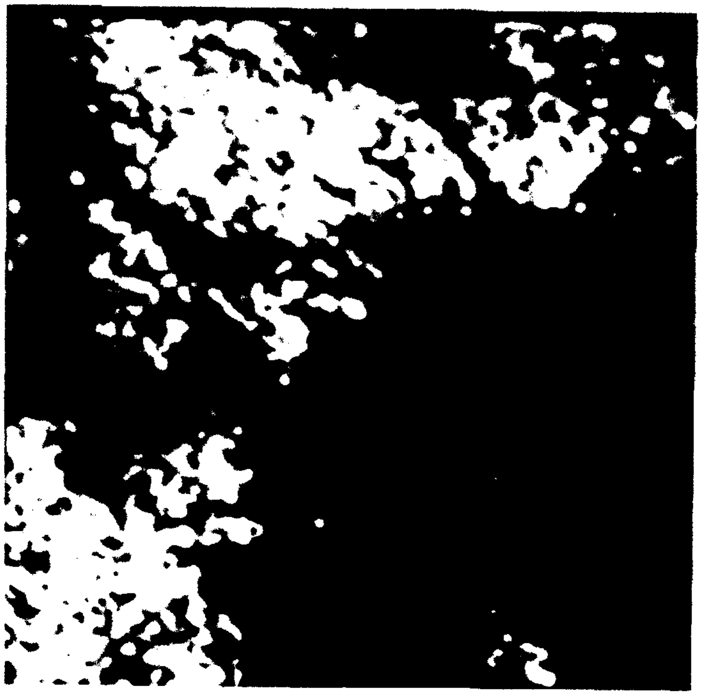


Figure 3. Root Mean Square Gabor Representation

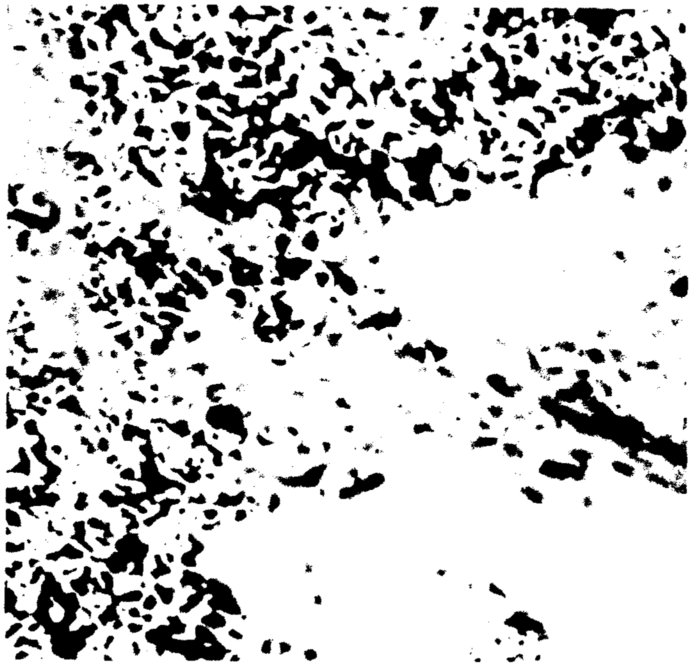


Figure 4. Orientation Distribution Gabor Representation

2.2 MORPHOLOGY

The Boundary Contour System (BCS) and Feature Contour System (FCS) models [4,5], are based primarily on psychophysical data. The BCS/FCS combination explains a large body of psychophysical data, and the elements of the model correspond closely to neurophysiological data about the visual cortex. Efficient versions of the BCS and FCS have been implemented for the purpose of reliably determining coherent regions in images corresponding to meteorological phenomena. The BCS determines boundaries and the FCS constructs regions from them. The regions then provide morphology information to the classifier.

2.2.1 Boundary Contour System (BCS) Implementation

On-center Off-surround Processing: The first stage of processing used a convolving filter constructed of a difference of two Gaussian filters. Such a filter closely approximates the spatial second derivative operation. The product of this filtering serves as the input to both the BCS and FCS systems.

Oriented Edge Detection: In our simulations we constructed convolving filters from the difference of two Gaussians of equal dimensions but with offset centers. We used six oriented filters: separation of the imagery into distinct orientation channels allows orientation-specific processing to be performed on each channel separately before the information is then recombined into a multi-orientation representation. This is an essential aspect of the algorithm which allows for certain powerful operations which could not be performed on the image as a whole.

First Competitive Stage: An edge enhancement operation is performed on each orientation plane.

Second Competitive Stage: The next step in the model is a second competitive stage wherein competition among all orientation channels occurs at each spatial location.

Oriented Cooperation: A cooperative operation is performed in each orientation channel to complete broken or incomplete edges. An oriented two-armed filter is convolved with each orientation plane, and a conjunction operation between the two arms produces a response in the filter only while it is straddled between aligned points. The family of cooperative filters is described by the following equation:

$$F^{(r)}_{x,y} = \pm\, e^{-2\left(\frac{\sqrt{x^2+y^2}}{\rho}-1\right)^2} \cdot \cos\left(\left|\operatorname{atan}\left(\frac{y}{x}\right)\right| - r\right)^P \tag{2}$$

where $F^{(r)}_{x,y}$ is the filter value at x,y for orientation r, r = 0.5, and P = 9.

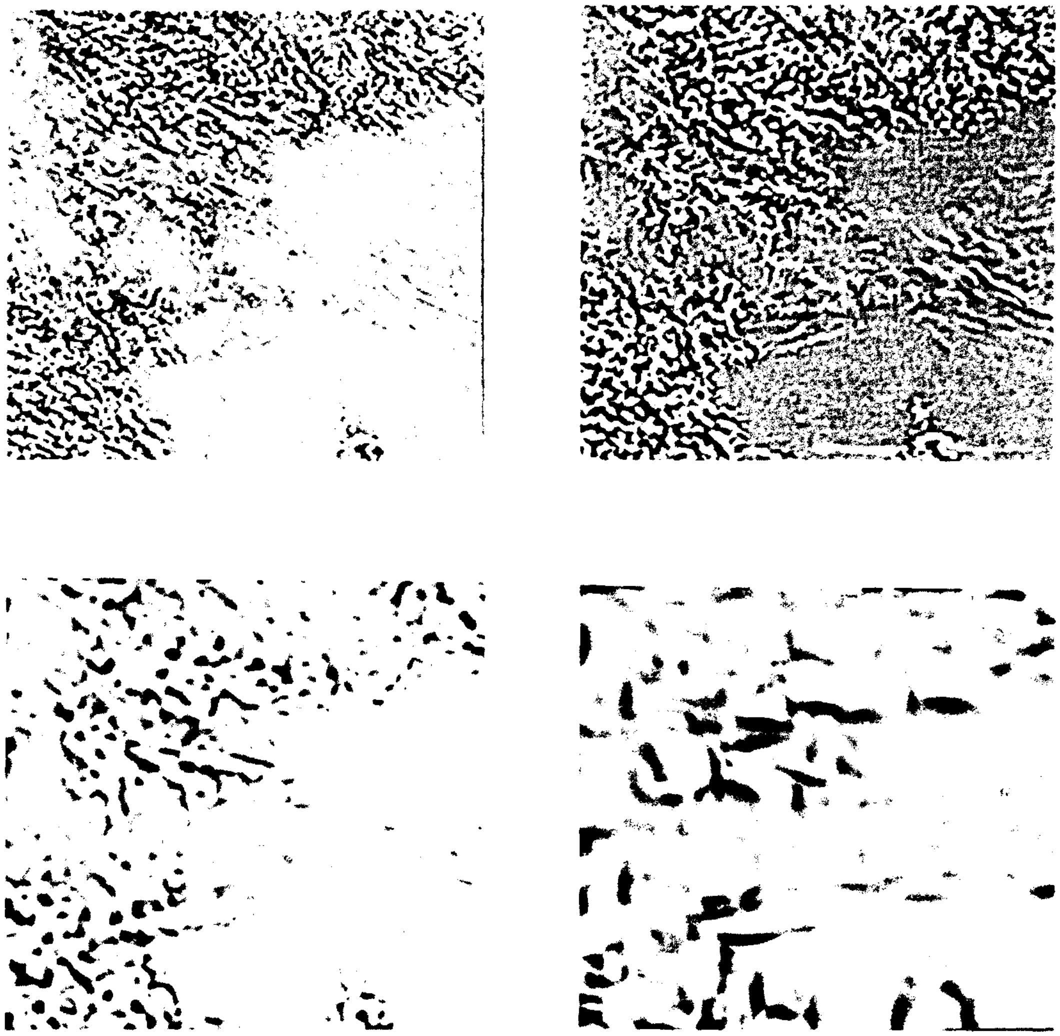
Feedback Loop: The images generated via the oriented filtering are recombined to close a large feedback loop. This feedback allows the results of the oriented cooperation to contribute to the oriented competition of the second competitive stage to perhaps shift the emphasis between oriented responses where appropriate.

2.2.2 Feature Contour System (FCS) Implementation

The region filling-in function of the Feature Contour System (FCS) begins with the same on-center off-surround image used by the BCS. The FCS allows color to diffuse freely in all directions within a region until it reaches strong boundaries developed by the BCS and exhibits properties observed in psychophysical data. In our system, the FCS is run at a number of spatial scales, providing morphology information to the classification system. The multi-spatial scale results for the image of figure 2 appear in figures 5-8.

Morphology is represented by sampling each of the spatial scales at a pixel location. Small clouds in relative isolation will only activate the highest spatial frequency FCS image. Small clouds that are part of larger cloud masses will activate FCS images at lower spatial frequencies as well. Large mixed cloud masses will activate all of the FCS scales. Large smooth cloud masses will activate only the largest scale, etc.

We ran a number of experiments that were identical except that some had the BCS morphology information and some did not. We found that the inclusion of the morphology information added a nine percent average performance improvement.



Figures 5-8. Morphology Channels 1-4 for June 6, 1991 1730 GMT

SECTION 3

EXPERIMENTAL PREPARATION

3.1 LAND/SEA MAPS

The infrared information is considerably different for land and ocean samples. Consequently, separation of the data into two separate tasks made sense to ease the learning task. Two neural networks were trained for each experiment: one for land and one for sea. We ran a number of experiments that showed improved learning and generalization performance using the separate data. In an eventual implementation, this approach could be extended to a range of different terrain types, e.g., snow, desert, etc. Because the satellite was moving east at the time of data collection, the best scenario would require a map that showed which image pixels were over land or sea for each day. The Phillips Laboratory, Geophysics Directorate provided MITRE with three map overlays of the northeast United States spaced evenly over the recording period. From these we generated three "land/sea" maps which indicate the type of background (land or sea) under each pixel for a third of the training days. To compensate for the uncertainty due to the satellite drift, an "undefined" band hugging all land masses was introduced, and the samples there were thrown out. This turned out to not be a problem because the database has so many pixel samples per day, for most cloud types, that the numbers of deleted data points were insignificant. In an ideal implementation, the land/sea information would be available for each specified time period and no undefined regions would be required. The land/sea map for June 10, 1991 at 1700 GMT appears in figure 9.

3.2 FEATURE VECTOR GENERATION

Feature vectors for training and testing used the format shown in column one of table 1. This format incorporated the Generalized Gabor representation described in section 2.1.1. Each feature vector represents data at one of the pixel locations identified as a particular cloud type by the meteorologists. Each data type is represented by a separate image plane. For each pixel location, there is a corresponding feature value for each of the data types in column one. To normalize the data, the mean and standard deviation of each data type were computed using all identified samples in the database across all 27 available days at 1700 GMT. Data for land and sea were isolated using the land/sea maps and two sets of statistics were calculated as shown in table 1. Separate normalized land and sea training/testing sets were generated by subtracting out the mean and dividing by the appropriate standard deviation for each data type at a subset of identified pixel locations.

The available number of samples across the 27 days was too large to include all of them. Moreover, the distributions of cloud types varied widely over the different days. In an

Figure 9. Land/Sea map for June 10, 1991 at 1700 GMT

so much in this 27 day set, it was difficult to achieve a perfectly even distribution. For example, when one cloud type appeared on only two days and another appeared on 23 days, it did not make sense to over sample the two days to match the 23 day sample because no new information would be added while enormous amounts of memory and training cycles would be consumed. We compromised by using even distributions among the present cloud types within a given day. The training set derived by concatenating the training sets from many days results in an uneven distribution. With a larger number of days, it would be possible to obtain a training set which removes the biases towards cloud types that occurred more frequently. For this experiment, we used 200 random samples of each cloud type from each day. If there were less than 200 samples present, then the samples present were oversampled to obtain 200 vectors. The number of cloud types present at a given hour

typically varied from one to five. Typical training set sizes were on the order of 14000 vectors. Typical testing set sizes were on the order of 800 vectors.

Table 1. Normalization Statistics

	Land		Sea	
Data Type	Mean	Standard Deviation	Mean	Standard Deviation
Visible	110.083	40.184	73.4685	43.7181
IR	98.0063	34.3616	104.209	31.5344
Gabor 1 RMS	353.883	479.91	178.765	968.264
Gabor 1 Ori	104.394	164.669	25.5906	289.525
Gabor 2 RMS	173.32	241.084	82.0621	616.953
Gabor 2 Ori	49.6255	82.418	30.0943	374.383
Gabor 3 RMS	86.8992	112.554	37.963	329.347
Gabor 3 Ori	13.6657	61.7071	16.589	215.911
Gabor 4 RMS	39.912	41.7574	16.7504	143.935
Gabor 4 Ori	0.564122	25.1688	7.6826	107.389
Morphology 1	3.92518	19.9179	0.133793	4.66539
Morphology 2	4.58013	21.6316	0.422905	6.87784
Morphology 3	369.515	985.301	115.875	583.83
Morphology 4	376.915	988.732	162.078	1000.77

3.3 CLASSIFIER TRAINING METHOD

For this experiment, layered feedforward neural networks with sigmoid non-linearities were trained to perform the cloud classification task. Initial architecture estimates for a few days were determined using a layered constructive learning algorithm [10] developed at MITRE which only added hidden units that improved generalization performance. It was found that the computational requirements for the constructive algorithm were prohibitive for the large experiment because of the overhead required to search for node candidates that improved generalization. Instead, we used the configuration of nodes and connectivity (but not the weight values) of the best performing of these architectures as the starting estimate for all of the experimental trials using a subtractive learning algorithm. This type of learning algorithm deletes connections and nodes to further tune the architecture and train the weights to the individual learning tasks. The standard starting network architecture had 14 input units, eight output units, eight fully connected hidden units in a first layer, and four fully connected hidden units in a second layer. Each hidden unit was connected to all of the output

units. The subtractive training algorithm used was a modified backpropagation learning rule described in the following.

As this experiment's goal was to explore the cross-validation capability of neural network classifiers, we sought to maximize the generalization performance of the classifier. Vapnik's theory of the VC *Dimension* [12] of a function approximator considers the maximum number H of vectors that can be shattered in an N-dimensional space. The theory states that as the number of training samples M gets small relative to H, the probability of generalization error goes up. To improve the generalization performance of the classifier function we are attempting to approximate, we try to reduce H (i.e., we reduce the number and complexity of classification boundaries to avoid fitting to noise) and/or increase M, if possible.

The first step we took to reduce the VC dimension was to reduce the number of weights in our networks. We implemented Weigand, Rumelhart's, and Huberman's Weight Elimination method [9], which drives less important weights to small values by adding a penalty term to the backpropagation learning cost function. The resulting cost function is equation three.

$$\sum_{k \in S} (\text{target}_k\text{-prediction}_k)^2 + \lambda \sum_{i,j} \left(\frac{\frac{w_{ij}^2}{w_0^2}}{1 + \frac{w_{ij}^2}{w_0^2}} \right) \qquad (3)$$

This cost function trades off a weight's contribution to reducing the sum squared error with the magnitude of the weight. A weight that is large and not contributing enough to the reduction of error is diminished. We used a value of 1.0 for w_0. Our implementation periodically pruned small weights from the network. If nodes became completely disconnected they were removed from the network. Removing the less important weights reduces the ability of the network to tune to noise in the training set and thus improves generalization performance. Removal of 130 or more weights was typical.

The next step to reduce the VC dimension was to reduce the dimensions of input vectors. In the cloud task, a reduced Gabor wavelet representation was implemented which shrunk the size of the vector from 66 to 14 real values. The final step we took did not reduce the VC dimension H, but rather improved generalization performance by increasing the number of training samples M by a factor of eight (see Feature Vector Generalization, above). These steps improved generalization performance on the cloud task by 20-30 percent, depending on the training set.

To improve the training performance, we implemented the Delta-Bar-Delta learning update rule [7] developed by Jacobs and Sutton. The new rule uses a separate learning constant for each weight in the network and keeps an exponentially decaying history of the error attributed to each weight. Thus the rate at which each weight is updated is based on a local estimate of its performance instead of the performance of the network as a whole.

Keeping statistics for ten trials on a simple problem, we found the average number of training epochs decreased from 659 to 49 (a 13-fold improvement) using the Delta-Bar-Delta learning rule.

SECTION 4

EXPERIMENTAL RESULTS

4.1 SINGLE TIME, MULTIPLE DAY EXPERIMENTS

We ran 54 leave-one-day-out experiments to test the generalization properties of the neural network method described above. For each of the 27 days of data available at 1700 GMT, training sets were constructed by concatenating all land or sea samples available on the remaining 26 days at 1700 GMT. The samples available for each day at 1700 comprised the testing set for that day. Two feedforward neural networks were trained for each day, one for land and one for sea. The training set and testing set results appear in table 2. All of the neural networks for this experiment were trained in parallel on separate Sun workstations using the MITRE Batch distributed computing system. Confusion Matrices for these runs appear in appendix I of this report[2].

4.2 ANALYSIS

The neural networks used in this experiment were trained using stochastic learning algorithms. As such, some of the networks achieved better results, either because the initial random weight settings of the network were well suited to the target function or because the learning had avoided falling into local minima. Results also vary because of the synoptic conditions present each day. In an ideal setting, each of the experiments would have been run many times and the results averaged to reduce the variance due to neural network training. That could not be done because of the large computational requirements for this experiment. Instead, the mean results of the single run experiments over the 27 different days are provided in table 2. These results are influenced by both training effects and actual performance on variable data conditions. Thus, an optimized training situation should be able to improve on the mean testing performance reported here.

The neural network training simulator updated the results whenever the testing set performance improved. This explains why the training set performance varies so much from day to day even though only 1/26th of the training set differs between any two days. For test sets such as Sea 6/07/91 1700 GMT, only one cloud type (clear) was present, and hence the network could attain excellent testing set performance very early in the training, when the training set performance was only 50.39 percent correct.

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2 The numbering scheme is zero-based for all confusion matrices presented in the appendices of this report. Thus, cloud type 1 corresponds to goal 0 and output 0, cloudtype 2 corresponds to goal 1 and output 1, etc.

Table 2. Single Time, Multiple Day Results (% Correct)

1991	Land		Sea	
Date	Training Set	Testing Set	Training Set	Testing Set
6/03	81.08	63.10	78.55	70.00
6/04	84.13	79.00	91.73	89.33
6/05	85.00	66.87	93.00	75.10
6/06	85.75	81.87	85.28	82.75
6/07	57.35	86.00	50.39	100.00
6/10	79.27	90.92	83.89	93.80
6/11	78.49	64.60	77.67	78.00
6/12	82.31	77.60	81.73	92.83
6/13	69.37	57.12	83.90	84.17
6/14	73.85	76.66	78.04	87.00
6/17	81.67	63.10	63.56	84.25
6/19	67.57	86.33	89.63	89.75
6/20	63.49	92.00	48.56	100.00
6/21	82.13	68.50	85.89	94.83
6/24	86.55	90.50	47.33	100.00
6/25	53.19	74.00	50.63	100.00
6/26	84.58	76.08	76.38	72.33
6/27	66.60	71.16	80.73	66.50
7/01	64.44	56.37	82.26	70.50
7/08	83.25	86.25	76.86	73.83
7/13	86.75	74.00	86.69	64.87
7/14	79.30	94.25	78.59	95.25
7/15	56.48	84.17	47.58	100.00
7/16	59.96	90.00	63.77	85.33
7/17	61.91	75.50	49.14	100.00
7/18	82.90	98.87	n/a	n/a
7/19	64.82	77.50	17.41	51.25
Mean	74.15	77.86	71.12	84.68

The correspondence of samples in the training set to those in the test sets must be carefully noted in assessing experimental results. In some cases, cloud types appearing on the test day did not occur during the other 26 days at that particular time. In other cases, the cloud type may have appeared during the prior 26 days, but the Synoptic activity might be sufficiently different that the examples of a single cloud type differ greatly. The confusion

matrix allows us to determine exactly how cloud types are misclassified. It also allows us to determine the cloud types present in the training and test sets.

Classification probabilities were computed using the 27 testing set confusion matrices produced in the 1700 GMT experiment[3] for both land and sea. Each value is computed by summing the number in the same matrix position for each experiment's testing set confusion matrix and dividing that sum by the total number of samples that occurred for that cloud type (i.e., in that row). These results appear in tables 3 and 4. Because many cloud types occur on only a few days in the data set, it is likely that outliers are having a great effect on the numbers that appear in these tables. As indicated above, some of the networks will have become stuck in local minima and so those results would not be indicative of the method's potential performance. Given that some cloud types only occur on a few days, one bad network could throw off the probabilities considerably. Thus, given the small number of sample days, these numbers should not be considered as absolute probabilities. Rather they should be seen as indicating where the confusions are likely to occur with this method along with a weak probability estimate. The reader can examine the individual matrices in appendix I to determine the relative influence of the individual experiments on these numbers.

For land, Small Scattered Cumulus (cl. 1) was confused most often with Cumulus (cl. 2) and less so with Stratocumulus (cl. 6) and Clear (cl. 8). It is quite possible that clear samples that occur between small scattered cumulus clouds have the same Gabor responses as Small Scattered Cumulus due to sampling error introduced by the size of the wavelets. It may be possible to avoid this by introducing a new class called clear-between-small-cumulus. For Cumulus (cl. 2) there is confusion between Small Scattered Cumulus (cl. 1) in the land case and Stratocumulus (cl. 6) for land and sea. Thin Cirrus (cl. 3) was most often confused with Clear (cl. 8) for sea. This may be due to the fact that the thinnest cirrus clouds and clear actually appear quite similar in the data representation used here: the Gabor wavelet responses may be minimal and enough of the IR value may be due to the background to make the samples similar. Thin Cirrus over cloud (cl. 5) was most often confused with Cumulus (cl. 2), but was also confused with Cirrus (cl. 4) and Stratocumulus (cl. 6). Here, the cloud that is in the background may be giving a stronger response than the thin cirrus clouds above. Stratocumulus (cl. 6) was most often confused with Cumulus (cl. 2). The technique had the most trouble discriminating between Altocumulus (cl. 7) and Stratocumulus (cl. 6). While this affect is present in the sea results, it is far less pronounced and some aspect of the background or climate may be making these classes look more similar over land. The technique was able to classify clear well on both land and sea.

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3 For the sea table, the results for 7/19 at 1700 GMT were left out. The network appears to have fallen into a poor local minima and is thus considered an outlier for this study.

Table 3. Land Cross-Validation Classification Probabilities for 27 Day 1700 GMT Experiment

	Machine Labeling							
Human Labeling	1	2	3	4	5	6	7	8
Small Scattered Cumulus: 1	.73	.15	.00	.00	.00	.06	.00	.06
Cumulus: 2	.06	.85	.00	.00	.01	.06	.01	.00
Thin Cirrus: 3	.06	.00	.56	.02	.01	.00	.00	.35
Cirrus: 4	.01	.00	.06	.75	.14	.01	.02	.01
Thin Cirrus over cloud: 5	.02	.13	.02	.09	.58	.09	.03	.03
Stratocumulus: 6	.00	.18	.00	.01	.02	.71	.07	.00
Altocumulus: 7	.05	.08	.00	.03	.00	.51	.33	.01
Clear: 8	.00	.00	.01	.00	.00	.00	.00	.99

Table 4. Sea Cross-validation Classification Probabilities for 27 Day 1700 GMT Experiment

	Machine Labeling							
Human Labeling	1	2	3	4	5	6	7	8
Small Scattered Cumulus: 1	.00	.00	.00	.00	.00	.00	.00	.00
Cumulus: 2	.00	.77	.01	.00	.00	.13	.09	.00
Thin Cirrus: 3	.00	.00	.65	.17	.03	.00	.00	.15
Cirrus: 4	.00	.00	.14	.80	.04	.00	.01	.00
Thin Cirrus over cloud: 5	.00	.00	.04	.02	.81	.10	.03	.00
Stratocumulus: 6	.00	.14	.00	.01	.01	.76	.09	.00
Altocumulus: 7	.00	.00	.00	.05	.02	.12	.80	.01
Clear: 8	.00	.00	.01	.00	.00	.00	.00	.98

The results for land are poorer and the range of confusions more diverse than for sea. The difficulty with land appears to be consistent with other cloud studies [3] and stems from the fact that the cloud systems over land can be influenced more by local geography (e.g., lakes, rivers, mountains) and are thus less homogenous than those over the sea. In addition, the background IR information will also tend to change with geography. There are a number

of possibilities for improving the land results. One approach would be to subdivide the land bodies into a particular type of terrain with separate training sets. Thus, as we now have a land and sea network, a coastal-land, mountain-land, and desert-land network might allow improved performance. Another approach would collect more training samples for land areas to capture more variability. Yet another approach would group land training samples on a monthly basis.

For all of the results, there is the potential for effects due to human judgment error in the training data. Sampling error due to the overlap of wavelet kernels at transition regions is a significant factor that could possibly be improved through the use of a different complement of wavelets. The relatively low resolution of the GOES data (1 KM/pixel) may be the cause of poor discrimination performance on certain cloud types having fine detail. Other cloud studies using better resolution (e.g., Advanced Very High Resolution Radiometer) imagery may achieve better overall results because certain cloud types appear similar at 1 KM resolution. The technique used here can readily be extended to imagery with higher resolution.

4.3 MULTIPLE TIME EXPERIMENTS

A key question to answer about the classification techniques used in this study concerns the amount of training data that would be required to scale up to operational use. Because the method is texture and IR temperature based it was expected that changes in cloud shadows during the day would effect the classification accuracy. Initial trials showed a performance fall off with test sets that differed greatly in time. The next set of experiments seeks to estimate the range of time that can be accurately covered by a classifier trained at a given time, and thus indicate how many classifiers would need to be trained to cover a full day.

The training set for 6/21/91 at 1700 from section 4.1 was used to train a classifier. Thus the training set was constructed by concatenating all land or sea samples available on the remaining 26 days at 1700 GMT. The classifier was then tested using data from 6/21/92 at 1430, 1500, 1600, 1730, and 1830 GMT. A more complete study would do a similar set of runs for each of the 27 days in the data set and average the results at each half hour, but resources did not allow that in this study. Hence these results should be considered as a result based on an extremely small sample which may be biased. Confusion Matrices for these runs appear in Appendix I of this report. The results are tabulated in table 5.

Table 5. Multiple Time Results (% Correct)

6/21/91	Land		Sea	
Time (GMT)	Training Set	Testing Set	Training Set	Testing Set
1430	44.25	56.75	44.31	100.0
1500	65.17	76.25	57.46	100.0
1600	61.46	86.00	49.72	83.67
1630	53.63	38.50	69.52	77.12
1700	82.13	68.50	85.89	94.83
1730	70.12	58.65	66.69	99.5
1830	32.00	67.95	71.17	80.00

4.3.1 Analysis

The testing set results for sea are significantly better at all times than those for land. However, the main results here are that (i) for sea, performance can fall off as much as 15-18% at an hour difference from the training time, but may be better than that, (ii) for land, results fall off from 8-13% within a half hour of the training time and up to 60% at one hour out.

The high test results for sea at 1430 and 1500 are due to a single class (clear) being present. The sea test result of 83.70 at 1600 results from the fact that only two classes are present besides clear and the method does best for those classes. Thus, these initial indications appear to suggest that a separate classifier would be needed at half hour intervals for land and at one hour or forty-five minute intervals for sea. One explanation is that the thermal mass of the sea may cause slower variation in the infrared than on land.

The possible finding that performance falls off at half hour intervals for land does not indicate that the method can't be scaled to operational use. Separate networks for each of the times could be trained. It is quite possible that hours symmetric around Zenith would have similar shadows and could be combined into a single classifier, but that test was not performed here. Samples from nearby times could also be mixed in the training set to produce a classifier that spans a number of hours. While the current dataset would allow this test, it was not performed as part of this study.

SECTION 5

DISCUSSION

The neural network classification technique presented in this study achieved results better than those achieved by Garand for sea samples. The test data used here is from completely unseen days, which strengthens the result. The fact that the same performance was reached without any analytic physical model features being included is of note. Limiting the complexity and number of such models can reduce the potential for modeling error and increase the portability of the resulting system.

Earlier studies [1,8] using high resolution imagery had better results than this study. It is clear that the current technique would extend to higher resolution imagery and should improve its performance considerably in that case. However, it should be clear that the Bankert study [1] used data from only four images: the test data in that study may not have been independent. The Lee study used only 3 classes; the 8 classes in the current study made for a considerably more difficult classification problem. As Lee does not specify the dates and times of the imagery used, it is impossible to judge whether the criteria for independence of that study meet the standards used here. Addition of physical models to the current approach may make sense if increased resolution does not improve the discrimination of certain cloud types. While the joint decision of two analysts was used as training data, human error may account for some of the machine classification error.

The techniques described here show promise for real time cloud classification[4]. The representation used by the approach is compact and can summarize large volumes of training data. Finished networks could be trained on small additional amounts of local training data to tune them to special local conditions.

4 Specialized hardware now exists which can run these algorithms in real time at a reasonable cost on standard workstations.

SECTION 6

FUTURE WORK

The research results presented here show the method works quite well with only learned features derived from neural network vision processing. There are several ways to improve the results. First, use of higher resolution imagery is recommended to allow better discrimination of cloud types by bringing out more textural details.

Second, we noticed that the meteorological analysts tended to look at the sequence of clouds leading up to the current hour. The existing database is ideally suited for a study which would take samples of a cloud in preceding hours to classify its type at the current hour.

Third, judicious choice of a few models of cloud physics to address specific discrimination problems may be inserted into the neural network model as done in [1].

Fourth, performance may be improved in discriminating between clear and thin cirrus by inserting a zero frequency gabor (i.e., a gaussian) into the set of preprocessed features. Since cirrus typically has little spatial frequency information associated with it, but does have spatial extent, the gaussian may help to integrate the weak luminance values and provide a feature set different from that observed for clear.

Last, larger sample sizes can probably be derived from this database. Vapnik's VC dimension theory shows that generalization performance can be improved by increasing the sample size. A larger training set capturing more variability can be generated from the current database by combining multiple hours of data. For example, samples from one hour before and one hour after Zenith can be combined to form a data set with twice the number of samples. This has the potential for greatly improved generalization performance because of the increased variability obtained by using more independent samples.

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APPENDIX

CLASSIFICATION MATRICES

Land 6/03/91 1700 GMT

1000 patterns 63.1% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	21	179	0	0	0	0	0	0
goal 2:	0	0	114	60	5	0	0	21
goal 3:	0	0	51	71	78	0	0	0
goal 4:	0	60	3	2	53	82	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21400 patterns 81.08% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3181	173	3	0	16	0	0	27
goal 1:	253	4288	0	0	58	394	7	0
goal 2:	0	0	881	57	0	0	0	62
goal 3:	0	0	149	1025	226	0	0	0
goal 4:	22	101	83	143	1993	48	7	3
goal 5:	7	233	0	15	72	2570	103	0
goal 6:	0	74	0	40	121	120	845	0
goal 7:	5	0	25	10	0	0	0	3960

Sea 6/03/91 1700 GMT

600 patterns 61.7% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	7	0	56	137	0	0
goal 5:	0	29	0	7	0	164	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 87.58% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	763	7	10	67	353	0	0
goal 2:	0	0	1076	151	22	0	0	151
goal 3:	0	0	255	1410	213	50	70	2
goal 4:	0	0	84	140	1086	62	24	4
goal 5:	0	94	0	2	4	1441	59	0
goal 6:	0	59	23	21	0	889	407	1
goal 7:	0	0	49	1	6	0	0	4344

Land 6/04/91 1700 GMT

600 patterns 79% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	107	0	1	5	85	2	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	16	0	0	174	10	0	0
goal 5:	0	0	0	2	5	193	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	0

21800 patterns 84.13% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3252	145	0	0	3	0	0	0
goal 1:	240	4423	0	0	97	240	0	0
goal 2:	4	0	1078	29	1	0	0	88
goal 3:	0	1	308	1131	136	24	0	0
goal 4:	24	137	84	367	1599	181	0	8
goal 5:	5	391	3	23	74	2114	185	0
goal 6:	0	101	0	136	131	206	626	0
goal 7:	4	0	75	2	1	0	0	4118

Sea 6/04/91 1700 GMT

600 patterns 89.33% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	156	0	40	4
goal 5:	0	0	0	0	0	199	1	0
goal 6:	0	0	0	0	0	19	181	0
goal 7:	0	0	0	0	0	0	0	0

13400 patterns 91.73% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1146	0	0	0	54	0	0
goal 2:	0	0	1207	85	31	0	0	77
goal 3:	0	1	275	1471	249	0	1	0
goal 4:	0	0	29	7	1322	24	18	0
goal 5:	0	25	0	0	6	1521	48	0
goal 6:	0	3	1	0	2	128	1065	1
goal 7:	0	0	38	1	0	1	0	4560

Land 6/05/91 1700 GMT

800 patterns 66.87% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	49	0	0	0	128	23	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	99	101	0	0	0
goal 5:	0	0	0	0	0	185	15	0
goal 6:	0	0	0	0	0	0	200	0
goal 7:	0	0	0	0	0	0	0	0

21600 patterns 85% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3079	285	2	0	34	0	0	0
goal 1:	198	4493	0	0	99	145	65	0
goal 2:	8	0	1109	0	65	0	0	18
goal 3:	0	0	292	843	444	0	21	0
goal 4:	8	130	56	23	2029	110	38	6
goal 5:	1	322	0	0	118	1889	470	0
goal 6:	0	51	0	0	140	15	794	0
goal 7:	10	0	61	0	3	0	0	4126

Sea 6/05/91 1700 GMT

1000 patterns 75.1% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	108	92	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	1	199	0	0	0
goal 5:	0	0	0	0	0	180	20	0
goal 6:	0	0	0	0	0	28	172	0
goal 7:	0	0	0	0	0	0	0	200

13000 patterns 93% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1000	0	0	0	0	0	0
goal 2:	0	0	1204	90	30	0	0	76
goal 3:	0	0	124	1561	301	0	14	0
goal 4:	0	1	14	24	1340	12	6	3
goal 5:	0	18	0	0	4	1540	38	0
goal 6:	0	0	0	0	11	109	1078	2
goal 7:	0	0	30	2	0	1	0	4367

Land 6/06/91 1700 GMT

800 patterns 81.87% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	105	90	1	0	1	0	3	0
goal 1:	2	183	0	0	8	7	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	17	0	0	4	179	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	4	0	1	0	0	195

21600 patterns 85.75% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3086	113	0	0	1	0	0	0
goal 1:	230	4290	1	2	112	362	3	0
goal 2:	22	0	966	13	9	0	0	190
goal 3:	0	0	367	825	346	6	42	14
goal 4:	13	122	87	29	2218	111	11	9
goal 5:	10	260	0	12	64	2328	126	0
goal 6:	0	97	3	9	152	196	743	0
goal 7:	3	0	32	0	0	0	0	3965

Sea 6/06/91 1700 GMT

600 patterns 84.6% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	108	89	0	0	0	3
goal 3:	0	0	0	200	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 85% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1094	0	0	0	106	0	0
goal 2:	0	0	695	18	1	0	0	486
goal 3:	0	1	330	1171	180	72	7	39
goal 4:	0	0	82	89	1257	159	8	5
goal 5:	0	59	0	0	0	1707	34	0
goal 6:	0	0	0	0	0	322	1073	5
goal 7:	0	0	0	3	0	4	0	4393

Land 6/07/91 1700 GMT

600 patterns 86% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	135	29	0	0	0	0	0	36
goal 1:	1	181	0	0	0	18	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 57 27% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2113	462	0	0	1	0	0	624
goal 1:	358	4165	5	6	51	228	1	186
goal 2:	38	0	0	27	0	0	0	1135
goal 3:	16	0	0	1023	0	72	24	465
goal 4:	192	603	4	744	8	439	0	540
goal 5:	137	1125	3	181	430	1102	11	11
goal 6:	31	200	1	193	16	701	37	21
goal 7:	9	0	0	5	0	0	0	3986

Sea 6/07/91 1700 GMT

200 patterns 100% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 50.39% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	393	4	240	27	423	93	20
goal 2:	0	16	0	716	0	67	0	601
goal 3:	0	197	0	1388	31	272	22	90
goal 4:	0	64	1	1237	81	152	61	4
goal 5:	0	283	1	371	105	405	628	7
goal 6:	0	208	3	427	135	294	330	3
goal 7:	0	11	4	22	0	1	4	4358

Land 6/10/91 1700 GMT

1400 patterns 90.92% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	200	0	0	0	0	0	0	0
goal 1:	23	123	0	0	50	4	0	0
goal 2:	0	0	194	6	0	0	0	0
goal 3:	0	0	15	185	0	0	0	0
goal 4:	0	5	5	4	183	1	0	2
goal 5:	0	4	0	0	6	188	2	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21000 patterns 79.27% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2861	336	0	0	3	0	0	0
goal 1:	290	4374	10	1	71	242	12	0
goal 2:	68	0	648	120	0	0	0	164
goal 3:	11	0	313	742	294	22	0	18
goal 4:	40	297	77	216	1511	178	45	36
goal 5:	10	486	1	0	124	2122	57	0
goal 6:	6	84	0	52	48	568	442	0
goal 7:	2	0	46	5	0	0	0	3947

Sea 6/10/91 1700 GMT

1000 patterns 92% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	152	10	10	0	0	28
goal 3:	0	0	20	177	3	0	0	0
goal 4:	0	0	0	0	200	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13000 patterns 86% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	883	0	0	0	108	9	0
goal 2:	0	7	890	139	46	0	0	118
goal 3:	0	1	96	1446	244	7	6	0
goal 4:	0	3	49	51	1231	52	11	3
goal 5:	0	38	0	0	49	1283	430	0
goal 6:	0	8	0	0	117	69	1205	1
goal 7:	0	4	19	8	0	0	0	4369

Land 6/11/91 1700 GMT

1000 patterns 64.6% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	153	2	0	12	33	0	0
goal 2:	69	0	24	0	0	0	0	107
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	2	117	0	81	0
goal 5:	0	0	0	0	14	175	11	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	23	0	0	0	0	177

21400 patterns 78.49% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2843	352	0	0	5	200	0	0
goal 1:	304	4387	2	1	59	229	18	0
goal 2:	0	0	884	25	6	0	0	85
goal 3:	14	0	327	898	270	60	1	30
goal 4:	119	305	116	198	1472	122	35	33
goal 5:	8	656	0	0	87	1854	195	0
goal 6:	6	77	0	16	61	557	483	0
goal 7:	2	0	18	3	1	0	0	3976

Sea 6/11/91 1700 GMT

1000 patterns 78% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	185	8	0	0	7	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	19	175	6	0	0	0
goal 4:	0	0	10	52	138	0	0	0
goal 5:	0	44	0	4	0	125	27	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	43	0	0	0	0	157

13000 patterns 77.67% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	674	0	1	10	315	0	0
goal 2:	0	0	1078	148	3	0	0	171
goal 3:	0	0	255	1278	216	49	2	0
goal 4:	0	6	48	137	1048	154	3	4
goal 5:	0	201	1	0	0	1398	0	0
goal 6:	0	135	1	58	128	813	262	3
goal 7:	0	2	36	2	0	0	0	4360

Land 6/12/91 1700 GMT

1000 patterns 77.6% correct

Test Classification Matrix

	Outputs 0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	198	0	0	2	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	4	0	13	181	2	0	0
goal 5:	0	1	0	0	2	197	0	0
goal 6:	0	0	0	0	0	200	0	0
goal 7:	0	0	0	0	0	0	0	200

21400 patterns 82.31% correct

Training Classification Matrix

	Outputs 0	1	2	3	4	5	6	7
goal 0:	3153	230	3	0	12	0	2	0
goal 1:	289	4143	7	0	140	417	4	0
goal 2:	30	0	994	38	8	0	0	130
goal 3:	0	0	249	789	539	12	7	4
goal 4:	29	159	61	28	1968	144	2	9
goal 5:	9	340	1	4	162	2273	11	0
goal 6:	0	96	0	17	225	303	359	0
goal 7:	3	0	57	3	0	0	0	3937

Sea 6/12/91 1700 GMT

600 patterns 92.83% correct

Test Classification Matrix

	Outputs 0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	200	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	16	170	14
goal 7:	0	0	7	6	0	0	0	187

13400 patterns 81.73% correct

Training Classification Matrix

	Outputs 0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1178	0	0	6	3	13	0
goal 2:	0	4	1236	63	6	0	0	91
goal 3:	0	5	241	1532	208	0	11	3
goal 4:	0	7	33	106	1083	0	166	5
goal 5:	0	224	0	43	11	537	984	1
goal 6:	0	14	0	66	41	7	1069	3
goal 7:	0	5	72	3	0	1	2	4317

Land 6/13/91 1700 GMT

800 patterns 57.12% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	4	179	0	0	0	17	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	119	0	3	0	78	0	0
goal 6:	0	0	0	29	0	171	0	0
goal 7:	0	0	0	0	0	0	0	200

21600 patterns 69.37% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2638	457	3	0	0	200	0	102
goal 1:	355	4251	41	7	56	270	8	12
goal 2:	58	0	194	557	0	0	0	391
goal 3:	23	0	140	1206	54	123	0	54
goal 4:	290	279	111	642	531	539	56	152
goal 5:	33	495	0	9	52	2143	68	0
goal 6:	48	113	3	2	17	768	49	0
goal 7:	1	0	1	26	0	0	0	3972

Sea 6/13/91 1700 GMT

600 patterns 84.17% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	200	0	0
goal 6:	0	3	0	57	4	7	129	0
goal 7:	0	18	3	1	0	2	0	176

13400 patterns 83.9% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1022	0	0	5	167	6	0
goal 2:	0	0	1152	130	13	0	0	105
goal 3:	0	1	229	1599	135	25	11	0
goal 4:	0	0	63	272	1149	89	23	4
goal 5:	0	102	0	2	2	1240	254	0
goal 6:	0	29	2	59	18	371	720	1
goal 7:	0	0	39	0	0	0	0	4361

Land 6/14/91 1700 GMT

1200 patterns 76.66% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	186	0	0	0	14	0	0	0
goal 1:	35	147	0	0	18	0	0	0
goal 2:	1	0	15	3	1	0	0	180
goal 3:	0	0	0	200	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	11	0	0	17	172	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21200 patterns 73.85% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2597	394	0	0	9	200	0	0
goal 1:	267	4389	1	4	89	243	7	0
goal 2:	69	0	221	332	95	0	0	283
goal 3:	17	0	153	676	368	55	2	129
goal 4:	85	270	32	163	1733	200	6	111
goal 5:	12	613	0	2	125	1911	137	0
goal 6:	6	120	0	2	118	806	148	0
goal 7:	4	0	1	7	5	0	0	3983

Sea 6/14/91 1700 GMT

600 patterns 87% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	184	0	0	0	0	16
goal 3:	0	0	52	138	10	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 78.04% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	722	19	2	48	409	0	0
goal 2:	0	0	922	115	18	0	0	145
goal 3:	0	1	218	1214	211	77	79	0
goal 4:	0	0	55	112	1221	201	7	4
goal 5:	0	140	11	2	1	1600	46	0
goal 6:	0	23	0	60	26	857	431	3
goal 7:	0	1	40	5	6	0	0	4348

Land 6/17/91 1700 GMT

1000 patterns 63.1% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	200	0	0
goal 1:	0	176	0	0	24	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	6	0	0	0	113	81	0	0
goal 5:	1	0	0	0	1	196	2	0
goal 6:	0	0	0	0	2	52	146	0
goal 7:	0	0	0	0	0	0	0	0

21400 patterns 81.67% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2885	307	0	0	8	0	0	0
goal 1:	244	4404	5	0	93	183	71	0
goal 2:	12	0	902	115	2	0	0	169
goal 3:	0	0	268	1005	294	21	1	11
goal 4:	19	237	75	183	1718	115	24	29
goal 5:	1	507	3	9	57	1814	409	0
goal 6:	14	63	0	99	92	107	625	0
goal 7:	5	0	68	0	1	0	0	4126

Sea 6/17/91 1700 GMT

800 patterns 84.25% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	176	23	1	0
goal 5:	0	0	0	0	13	187	0	0
goal 6:	0	0	0	0	18	71	111	0
goal 7:	0	0	0	0	0	0	0	200

13200 patterns 63.56% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	208	3	9	193	301	444	42
goal 2:	0	0	0	664	83	0	0	653
goal 3:	0	24	1	1432	369	28	98	48
goal 4:	0	0	0	331	927	10	128	4
goal 5:	0	21	3	0	83	908	580	5
goal 6:	0	60	1	2	160	429	544	4
goal 7:	0	9	0	20	0	0	0	4371

Land 6/19/91 1700 GMT

600 patterns 86.33% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	130	64	6	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	3	9	188	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 67.57% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2698	449	0	0	0	200	0	53
goal 1:	458	4429	5	9	64	183	42	10
goal 2:	88	0	39	552	0	0	0	521
goal 3:	25	0	4	1126	100	7	0	138
goal 4:	189	455	25	854	725	128	2	222
goal 5:	20	774	2	1	153	1621	229	0
goal 6:	42	138	2	110	45	744	117	2
goal 7:	3	0	9	12	0	0	0	3976

Sea 6/19/91 1700 GMT

400 patterns 89.75% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	174	24	2	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	185	15	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	0

13600 patterns 89.63% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1137	0	0	0	63	0	0
goal 2:	0	0	1187	131	0	0	0	82
goal 3:	0	2	119	1651	12	14	2	0
goal 4:	0	3	54	392	966	128	52	5
goal 5:	0	48	0	9	2	1425	116	0
goal 6:	0	4	0	1	14	92	1284	5
goal 7:	0	1	55	0	2	1	0	4541

Land 6/20/91 1700 GMT

800 patterns 92% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	185	0	0	0	0	0	0	15
goal 1:	45	154	0	0	0	0	0	1
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	197	3	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21600 patterns 63.49% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2411	520	0	0	0	200	0	69
goal 1:	429	4270	0	5	23	228	41	4
goal 2:	63	0	0	516	5	0	0	616
goal 3:	20	0	0	936	223	6	11	204
goal 4:	180	670	0	427	706	152	295	170
goal 5:	27	718	0	3	39	1996	216	1
goal 6:	31	139	0	107	40	540	342	1
goal 7:	2	2	0	6	1	0	0	3989

Sea 6/20/91 1700 GMT

200 patterns 100% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 48.56% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	138	18	58	8	44	844	0	90
goal 2:	0	0	212	30	3	41	3	1111
goal 3:	3	0	641	91	177	766	8	314
goal 4:	0	0	247	58	512	740	11	32
goal 5:	25	0	30	15	214	1506	0	10
goal 6:	13	0	24	3	277	1082	0	1
goal 7:	0	6	0	20	7	0	4	4363

Land 6/21/91 1430 GMT

800 patterns 56.75% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	62	55	27	1	33	1	0	21
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	198	2	0	0
goal 4:	0	0	0	0	199	1	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 44.25% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	1147	301	0	1	67	0	0	1884
goal 1:	618	2667	70	322	449	105	34	735
goal 2:	53	0	0	0	325	0	0	822
goal 3:	46	0	13	0	958	228	0	355
goal 4:	64	188	46	62	1189	468	48	335
goal 5:	185	590	36	246	460	1072	169	242
goal 6:	35	85	61	15	230	678	88	8
goal 7:	0	0	0	0	0	0	0	4000

Sea 6/21/91 1430 GMT

200 patterns 100% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 44.31% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	76	49	21	105	691	58
goal 2:	0	0	74	156	206	12	51	901
goal 3:	0	0	154	435	425	111	447	228
goal 4:	0	0	107	755	101	38	588	11
goal 5:	0	1	102	495	17	147	1004	34
goal 6:	0	0	27	394	11	17	927	24
goal 7:	0	17	2	0	4	0	0	4377

Land 6/21/91 1500 GMT

800 patterns 76.25% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	1	177	11	0	6	5	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	193	7	0	0	0
goal 4:	0	0	9	146	45	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 65.17% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2825	329	13	0	18	200	0	15
goal 1:	330	4340	1	0	92	214	21	2
goal 2:	33	0	805	193	9	0	0	160
goal 3:	2	0	348	897	319	6	2	26
goal 4:	22	157	105	218	1647	152	72	27
goal 5:	5	613	0	0	99	2076	207	0
goal 6:	7	112	0	4	137	530	[illegible]	0
goal 7:	2	0	49	0	0	0	0	3949

Sea 6/21/91 1500 GMT

400 patterns 100% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	200	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 57.46% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	230	3	66	3	399	285	14
goal 2:	0	0	1	647	0	0	1	751
goal 3:	1	1	0	1550	111	11	52	74
goal 4:	0	0	1	1109	285	46	153	6
goal 5:	9	212	0	76	17	880	603	3
goal 6:	6	128	2	25	154	321	728	36
goal 7:	10	10	0	0	0	0	0	4380

Land 6/21/91 1600 GMT

600 patterns 86% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	9	169	3	0	5	12	2	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	2	15	5	24	153	0	1	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	2	0	0	0	0	198

21800 patterns 61.46% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3071	299	0	0	28	2	0	0
goal 1:	256	3854	0	0	156	695	39	0
goal 2:	365	0	678	62	47	0	0	48
goal 3:	108	5	154	748	468	0	113	4
goal 4:	134	283	27	24	1733	50	144	5
goal 5:	284	486	0	0	153	1508	568	1
goal 6:	4	45	0	0	32	35	1084	0
goal 7:	39	0	15	0	4	0	0	3942

Sea 6/21/91 1600 GMT

600 patterns 83.67% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	102	96	0	0	2
goal 4:	0	0	0	0	200	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 49.72% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	401	34	218	49	12	157	129
goal 2:	0	46	12	275	64	0	1	1002
goal 3:	0	27	60	648	817	0	35	213
goal 4:	2	50	18	624	760	16	107	23
goal 5:	2	267	146	165	319	45	850	6
goal 6:	7	108	85	151	462	34	538	15
goal 7:	13	1	0	0	0	0	0	4386

Land 6/21/91 1630 GMT

1000 patterns 38.50% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	200	0	0	0	0	0	0
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	200	0	0	0
goal 4:	0	122	0	0	78	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	1	37	0	0	6	0	0	156

21800 patterns 53.63% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2715	304	0	0	0	218	0	163
goal 1:	732	3711	10	0	9	355	8	175
goal 2:	217	0	3	0	307	7	0	666
goal 3:	109	0	4	0	416	830	0	241
goal 4:	116	219	8	0	684	1161	2	210
goal 5:	29	821	8	0	5	2128	0	9
goal 6:	45	63	0	0	2	1089	0	1
goal 7:	15	0	0	0	0	0	0	3985

Sea 6/21/91 1630 GMT

800 patterns 77.12% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	17	183	0	0	0
goal 4:	0	0	0	0	200	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 69.52% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	671	3	5	12	309	0	0
goal 2:	0	2	573	382	0	0	0	443
goal 3:	0	50	222	1211	246	6	42	23
goal 4:	0	57	58	245	1053	76	107	4
goal 5:	0	426	1	2	17	1040	314	0
goal 6:	0	176	0	0	129	390	699	6
goal 7:	0	4	3	1	0	0	0	4392

Land 6/21/91 1700 GMT

600 patterns 68.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	197	0	0	0	0	2	1
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	102	0	0	33	1	2	62
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	13	0	6	0	0	181

21800 patterns 82.13% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3167	219	0	0	14	0	0	0
goal 1:	249	4335	4	1	91	237	83	0
goal 2:	24	0	673	264	6	0	0	233
goal 3:	0	0	145	1199	192	0	63	1
goal 4:	9	111	45	265	1766	102	92	10
goal 5:	8	390	0	2	70	1737	793	0
goal 6:	0	64	0	12	57	23	1044	0
goal 7:	3	0	12	1	1	0	0	3983

Sea 6/21/91 1700 GMT

600 patterns 94.83% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	1	199	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	30	0	0	0	0	170

13400 patterns 85.89% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1000	0	0	0	0	0	0
goal 2:	0	0	1053	182	18	0	0	147
goal 3:	0	0	202	1351	247	0	0	0
goal 4:	0	11	26	66	1469	2	26	0
goal 5:	0	174	0	2	87	1159	375	3
goal 6:	0	156	1	1	94	51	1096	1
goal 7:	0	0	9	10	0	0	0	4381

Land 6/21/91 1730 GMT

800 patterns 70.12% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	119	47	25	0	0	0	0	9
goal 1:	2	111	32	6	0	42	0	7
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	7	38	19	131	2	0	3
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 58.65% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2379	31	1	0	0	200	0	139
goal 1:	467	4008	25	11	29	320	32	108
goal 2:	53	0	43	0	197	0	0	907
goal 3:	34	0	51	6	1161	0	0	348
goal 4:	128	261	52	4	1577	114	3	261
goal 5:	20	662	7	2	150	2091	12	56
goal 6:	107	75	0	0	310	669	27	11
goal 7:	3	4	6	0	0	0	0	3987

Sea 6/21/91 1730 GMT

600 patterns 99.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	199	1	0	0	0	0
goal 3:	0	0	2	198	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 66.69% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	330	13	17	0	343	286	11
goal 2:	0	0	803	227	0	0	0	370
goal 3:	0	0	277	1260	228	9	7	19
goal 4:	0	1	197	677	450	219	52	4
goal 5:	0	151	17	7	0	1206	418	1
goal 6:	2	113	5	1	74	577	622	[illegible]
goal 7:	0	0	5	1	0	0	0	4391

Land 6/21/91 1830 GMT

800 patterns 32% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	56	144	0	0	0	0	0	0
goal 1:	1	199	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	14	181	0	0	5	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	40	149	0	0	11	0	0	0

21800 patterns 67.95% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3202	163	0	0	35	0	0	0
goal 1:	349	4226	8	0	145	253	19	0
goal 2:	9	0	1057	60	6	0	0	68
goal 3:	0	0	309	958	316	4	11	2
goal 4:	29	136	67	44	2020	74	27	3
goal 5:	2	610	0	19	94	1838	437	0
goal 6:	10	118	0	63	62	53	894	0
goal 7:	9	0	106	0	3	0	0	3832

Sea 6/21/91 1830 GMT

600 patterns 80% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	154	46	0	0	0	0
goal 3:	0	0	74	126	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 71.17% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	561	18	15	15	380	0	11
goal 2:	0	0	696	357	1	1	0	345
goal 3:	0	0	222	1272	280	9	0	17
goal 4:	0	4	70	232	1137	132	21	4
goal 5:	0	408	3	4	33	1118	231	3
goal 6:	0	186	0	26	154	487	543	4
goal 7:	0	5	5	1	0	0	0	4389

Land 6/24/91 1700 GMT

600 patterns 90.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	164	36	0	0	0	0	0	0
goal 1:	3	179	0	0	5	13	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 86.55% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3073	111	1	0	15	0	0	0
goal 1:	399	4159	0	0	136	274	32	0
goal 2:	18	0	1094	54	1	0	0	33
goal 3:	2	0	103	1219	255	2	19	0
goal 4:	21	100	32	124	2090	181	46	6
goal 5:	0	382	0	9	86	2304	219	0
goal 6:	3	66	0	0	57	82	992	0
goal 7:	3	0	41	16	3	0	0	3937

Sea 6/24/91 1700 GMT

200 patterns 67.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 69.15% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	136	13	35	88	609	162	157
goal 2:	0	3	82	116	41	83	14	1061
goal 3:	9	16	71	131	524	1001	17	231
goal 4:	0	25	6	68	632	824	20	25
goal 5:	0	209	1	2	330	1168	68	22
goal 6:	0	150	0	0	313	880	18	39
goal 7:	3	0	30	0	2	0	0	4365

Land 6/25/91 1700 GMT

600 patterns 74% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	53	143	0	0	0	0	0	4
goal 1:	3	191	0	0	1	1	2	2
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 53.19% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	1626	299	0	0	24	209	20	1022
goal 1:	734	3635	4	100	59	143	71	254
goal 2:	0	0	0	1	169	0	0	1030
goal 3:	0	0	0	96	1091	67	0	346
goal 4:	136	467	17	110	730	496	13	631
goal 5:	74	1108	1	72	66	1466	194	19
goal 6:	29	128	1	44	125	817	48	8
goal 7:	0	0	0	0	4	0	0	3996

Sea 6/25/91 1700 GMT

200 patterns 100% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 50.63% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	667	0	197	10	5	279	42
goal 2:	0	8	1	445	215	0	19	712
goal 3:	0	136	1	1413	164	4	166	116
goal 4:	0	80	0	1250	27	1	236	6
goal 5:	0	734	0	134	9	84	823	16
goal 6:	8	605	0	270	36	16	445	20
goal 7:	0	11	0	13	12	13	0	4351

Land 6/26/91 1700 GMT

1200 patterns 76.08% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	187	13	0	0	0	0	0	0
goal 1:	28	161	0	0	1	0	10	0
goal 2:	0	0	198	2	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	11	0	0	0	148	40	1	0
goal 5:	0	1	3	0	8	19	169	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21200 patterns 84.58% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2900	297	2	0	1	0	0	0
goal 1:	72	4305	4	0	90	523	6	0
goal 2:	2	0	826	18	11	0	0	143
goal 3:	0	0	307	818	465	1	1	8
goal 4:	9	94	71	85	1948	175	10	8
goal 5:	7	182	0	8	62	2469	72	0
goal 6:	3	64	0	59	149	216	709	0
goal 7:	2	0	40	0	1	0	0	3957

Sea 6/26/91 1700 GMT

600 patterns 72.33% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	34	133	33	0	0	0
goal 3:	0	0	0	200	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 76.38% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	917	7	19	105	152	0	0
goal 2:	0	0	764	149	0	0	0	287
goal 3:	0	3	213	1313	191	64	6	10
goal 4:	0	1	61	360	1092	72	10	4
goal 5:	0	311	0	32	14	1169	274	0
goal 6:	0	107	0	82	90	491	624	6
goal 7:	0	5	30	2	7	0	0	4356

Land 6/27/91 1700 GMT

1200 patterns 71.16% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	195	0	0	0	0	0	0	5
goal 1:	14	184	0	0	0	2	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	4	0	0	191	0	0	0	5
goal 4:	2	0	0	84	72	42	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	3	6	0	2	0	177	12	0
goal 7:	0	0	0	0	0	0	0	200

21200 patterns 66.6% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2482	459	0	0	0	200	0	59
goal 1:	428	4280	0	3	4	233	13	39
goal 2:	105	0	0	672	0	0	0	423
goal 3:	19	0	0	994	136	211	0	40
goal 4:	106	665	0	535	331	500	35	228
goal 5:	10	912	0	0	6	2024	48	0
goal 6:	35	136	0	25	0	749	51	4
goal 7:	6	3	0	33	0	0	0	958

Sea 6/27/91 1700 GMT

600 patterns 65.16% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	199	0	0	0	0	1
goal 3:	0	0	200	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13400 patterns 72.43% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	903	0	26	22	249	0	0
goal 2:	0	0	962	101	2	0	0	135
goal 3:	0	0	30	1544	218	1	7	0
goal 4:	0	19	89	181	1237	63	7	4
goal 5:	0	325	8	61	20	1165	221	0
goal 6:	0	91	18	183	167	263	666	12
goal 7:	0	1	55	0	1	1	0	4342

Land 7/01/91 1700 GMT

800 patterns 56.37% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	187	0	0	0	0	0	0	13
goal 1:	23	176	0	0	0	0	0	1
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	1	97	6	0	71	3	0	22
goal 5:	4	158	0	8	6	17	2	5
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	0

21600 patterns 64.44% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	1951	554	0	0	289	0	0	406
goal 1:	490	3831	58	14	184	230	7	186
goal 2:	49	0	10	7	530	0	0	604
goal 3:	2	2	98	215	1065	159	0	59
goal 4:	144	458	50	96	944	444	25	239
goal 5:	4	992	1	41	872	860	14	16
goal 6:	5	275	4	9	269	628	4	6
goal 7:	1	0	0	1	29	0	0	4169

Sea 7/01/91 1700 GMT

800 patterns 70.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	165	0	0	0	0	35
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	196	0	0	0	0	0	4
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	1	0	0	0	0	199

13200 patterns 82.26% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	982	0	0	2	0	16	0
goal 2:	0	0	931	127	43	0	0	99
goal 3:	0	9	247	1417	267	29	31	0
goal 4:	0	65	57	125	1268	75	9	1
goal 5:	0	253	0	9	35	1068	235	0
goal 6:	0	53	0	34	219	226	864	4
goal 7:	0	1	69	1	0	0	0	4329

Land 7/08/91 1700 GMT

800 patterns 86.25% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	194	0	0	0	6	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	7	0	6	109	39	7	32	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	11	0	0	0	188	1	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	1	0	0	0	0	0	0	199

21600 patterns 83.25% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3225	167	7	0	1	0	0	0
goal 1:	281	4271	1	0	132	304	11	0
goal 2:	0	0	1172	0	0	0	0	28
goal 3:	6	0	457	924	0	9	3	1
goal 4:	34	134	207	442	1384	344	44	11
goal 5:	10	378	0	26	62	2161	163	0
goal 6:	0	63	0	23	14	155	945	0
goal 7:	8	0	91	0	0	0	0	3901

Sea 7/08/91 1700 GMT

600 patterns 89.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	4	0	147	38	0	11	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	2	0	0	0	1	192	5
goal 7:	0	0	2	0	0	0	0	198

13400 patterns 77.67% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1065	0	0	0	112	23	0
goal 2:	0	0	986	301	34	2	0	77
goal 3:	0	0	153	1518	122	0	7	0
goal 4:	0	0	11	295	1260	2	28	4
goal 5:	0	212	0	26	50	520	992	0
goal 6:	0	15	0	227	40	197	718	3
goal 7:	0	0	58	0	0	0	0	4342

Land 7/13/91 1700 GMT

1000 patterns 74% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	200	0	0	0	0	0	0	0
goal 1:	97	103	0	0	0	0	0	0
goal 2:	0	0	186	0	0	0	0	14
goal 3:	0	0	35	165	0	0	0	0
goal 4:	40	7	37	27	86	0	0	3
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	0

21400 patterns 86.75% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3084	110	0	0	6	0	0	0
goal 1:	191	4481	0	0	91	191	46	0
goal 2:	0	0	587	365	3	0	0	45
goal 3:	0	0	32	1133	222	8	5	0
goal 4:	3	164	5	189	1867	133	36	3
goal 5:	2	416	0	6	84	2361	131	0
goal 6:	0	76	0	11	115	95	903	0
goal 7:	4	0	39	4	4	0	0	4149

Sea 7/13/91 1700 GMT

800 patterns 73.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	70	4	0	0	0	126
goal 3:	0	5	1	176	0	0	18	0
goal 4:	0	0	58	0	142	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13200 patterns 87.37% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1176	0	0	0	24	0	0
goal 2:	0	0	1021	91	31	0	0	57
goal 3:	0	28	183	1333	245	8	3	0
goal 4:	0	0	1	21	1336	34	7	1
goal 5:	0	288	1	0	193	1054	264	0
goal 6:	0	22	1	0	27	73	1274	3
goal 7:	0	0	59	2	0	0	0	4339

Land 7/14/91 1700 GMT

400 patterns 94.25% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	196	0	0	0	4	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	19	0	0	0	181	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	0

22000 patterns 79.3% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	3059	324	5	0	12	0	0	0
goal 1:	320	4252	7	1	98	306	16	0
goal 2:	34	0	972	19	29	0	0	146
goal 3:	0	0	352	910	319	0	0	19
goal 4:	20	272	98	272	1692	204	11	31
goal 5:	5	405	2	0	125	2210	53	0
goal 6:	6	100	1	0	214	664	215	0
goal 7:	3	0	58	3	0	0	0	4136

Sea 7/14/91 1700 GMT

400 patterns 95.25% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	19	0	0	0	181	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13600 patterns 78.59% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	1106	0	0	41	40	13	0
goal 2:	0	0	1198	81	48	0	0	73
goal 3:	0	0	242	1468	286	4	0	0
goal 4:	0	1	33	214	1133	201	14	4
goal 5:	0	144	0	1	11	1415	29	0
goal 6:	0	5	0	291	60	958	27	59
goal 7:	0	3	55	1	0	0	0	4341

Land 7/15/91 1700 GMT

600 patterns 90% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	121	0	0	0	0	0	0	79
goal 1:	15	184	0	0	0	0	0	1
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 59.96% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	1656	387	0	0	235	0	1	921
goal 1:	429	3852	15	31	20	293	101	259
goal 2:	28	0	0	216	481	0	6	469
goal 3:	0	0	4	111	1023	6	354	102
goal 4:	87	252	0	267	1183	236	318	257
goal 5:	11	746	0	10	784	1406	43	0
goal 6:	18	59	0	0	199	751	168	5
goal 7:	12	0	0	23	29	0	0	3936

Sea 7/15/91 1700 GMT

200 patterns 85.33% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 63.77% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	130	288	124	365	211	67	15
goal 2:	0	26	1	384	16	27	84	862
goal 3:	0	83	2	1066	46	185	452	166
goal 4:	0	64	13	980	123	163	235	22
goal 5:	0	220	31	303	310	843	86	7
goal 6:	0	157	32	432	149	576	48	6
goal 7:	0	1	3	10	10	0	20	4356

Land 7/16/91 1700 GMT

600 patterns 80.0% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	177	0	0	0	0	0	0	23
goal 1:	28	163	0	0	0	1	0	8
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21800 patterns 59.96% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2334	337	0	0	0	201	0	328
goal 1:	490	4211	3	5	30	121	14	126
goal 2:	22	0	0	18	0	0	0	1160
goal 3:	14	0	0	787	67	67	0	665
goal 4:	133	654	0	631	186	368	6	622
goal 5:	4	1440	0	10	10	1417	107	12
goal 6:	9	278	0	2	6	741	141	23
goal 7:	1	0	0	0	4	0	0	3995

Sea 7/16/91 1700 GMT

200 patterns 85.33% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 63.77% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	130	288	124	365	211	67	15
goal 2:	0	26	1	384	16	27	84	862
goal 3:	0	83	2	1066	46	185	452	166
goal 4:	0	64	13	980	123	163	235	22
goal 5:	0	220	31	303	310	843	86	7
goal 6:	0	157	32	432	149	576	48	6
goal 7:	0	1	3	10	10	0	20	4356

Land 7/17/91 1700 GMT

800 patterns 75.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	178	3	0	0	0	0	0	19
goal 1:	1	192	0	0	0	0	0	7
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	2	155	0	3	0	34	0	6
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21600 patterns 61.91% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	1917	440	0	0	16	204	0	623
goal 1:	250	4039	2	5	16	327	34	327
goal 2:	13	0	0	199	139	44	0	805
goal 3:	3	0	1	904	343	76	0	273
goal 4:	54	399	0	544	799	358	5	441
goal 5:	2	685	1	7	206	1787	93	19
goal 6:	3	91	0	29	188	808	71	10
goal 7:	135	0	4	7	0	0	0	3854

Sea 7/17/91 1700 GMT

200 patterns 100% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	0	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

13800 patterns 49.14% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	39	141	46	320	64	566	24
goal 2:	0	1	42	848	0	19	18	472
goal 3:	0	3	7	1302	57	529	65	37
goal 4:	0	15	21	883	345	179	145	12
goal 5:	6	133	5	46	706	325	546	33
goal 6:	7	33	2	239	403	317	387	12
goal 7:	0	6	2	31	15	0	4	4342

Land 7/18/91 1700 GMT

800 patterns 98.87% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	200	0	0	0	0	0	0	0
goal 1:	1	198	0	0	0	1	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	4	0	0	193	3	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	0	0	0	0	0	0	0
goal 7:	0	0	0	0	0	0	0	200

21600 patterns 82.9% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2939	151	0	0	110	0	0	0
goal 1:	227	4424	0	0	182	164	3	0
goal 2:	0	0	478	342	18	0	0	362
goal 3:	0	0	14	1186	388	0	4	8
goal 4:	40	147	17	101	1978	93	10	14
goal 5:	8	807	0	0	105	2002	78	0
goal 6:	0	103	0	0	137	39	921	0
goal 7:	5	0	8	7	0	0	0	3980

Land 7/19/91 1700 GMT

800 patterns 77.5% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	183	3	0	0	0	0	0	14
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	52	94	0	0	0	8	37	9
goal 7:	0	0	0	0	0	0	0	200

21600 patterns 64.82% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	2427	461	0	0	0	200	0	112
goal 1:	427	4115	0	20	16	348	9	65
goal 2:	180	0	0	353	0	0	0	667
goal 3:	162	0	0	758	176	196	128	180
goal 4:	390	206	0	293	461	637	317	296
goal 5:	18	705	0	0	7	2258	11	1
goal 6:	2	1	0	0	2	994	1	0
goal 7:	6	0	0	12	0	0	0	3982

Sea 7/19/91 1700 GMT

400 patterns 50% correct

Test Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	200	0	0	0	0	0	0
goal 2:	0	0	0	0	0	0	0	0
goal 3:	0	0	0	0	0	0	0	0
goal 4:	0	0	0	0	0	0	0	0
goal 5:	0	0	0	0	0	0	0	0
goal 6:	0	58	0	0	0	139	0	3
goal 7:	0	0	0	0	0	0	0	0

13600 patterns 80.7% correct

Training Classification Matrix

Outputs

	0	1	2	3	4	5	6	7
goal 0:	0	0	0	0	0	0	0	0
goal 1:	0	814	0	8	118	43	17	0
goal 2:	0	0	1060	122	25	0	0	193
goal 3:	0	0	249	1486	190	55	18	2
goal 4:	0	18	75	311	1159	23	10	4
goal 5:	0	251	0	60	27	960	502	0
goal 6:	0	8	0	113	11	114	951	3
goal 7:	0	4	43	4	0	0	0	4549